Enhancing US Thyroid Images for Cancer Detection: Pre-Processing Techniques

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Abstract: Thyroid cancer detection using ultrasound (US) images requires efficient preprocessing techniques to enhance image quality and suppress noise. This research introduces a preprocessing technique for US thyroid images in MATLAB, aiming to apply and measure several filtering methods. The filters are chosen respectively as average, adaptive median, mean, and Wiener to handle different types of noise and preserve necessary details for analysis. Applying these filters one by one enables us to identify and highlight clear information while maintaining the accuracy of medical testing. The effectiveness of filtering techniques for noise reduction and image enhancement is shown in experimental results, which prepares the way for accurate thyroid cancer detection. According to the findings, preprocessing plays a key role in enhancing the diagnostic ability of US thyroid machines.

Keywords: *Preprocessing, Noise Reduction, Filtration Techniques, Thyroid Cancer.*

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I. INTRODUCTION

Thyroid cancer detection using machine learning (ML) techniques involves analysing medical images, typically ultrasound (US) or histopathological images, and applying various computational models to identify patterns indicative of malignancy. The primary goal is to accurately differentiate between benign and malignant thyroid nodules, thereby assisting clinicians in making accurate diagnoses. To develop a machine learning-based system for thyroid cancer detection that can automatically analyse ultrasound images (or other imaging modalities like CT/MRI) and classify thyroid nodules as benign or malignant.

The system flow diagram for thyroid cancer detection using machine learning typically includes the following key steps:

➢ *Data Collection:*

The collection of data is a key component of the proposed work; therefore, we have obtained thyroid ultrasound images from an open repository.

➢ *Image Preprocessing:*

Image preprocessing involves a series of steps to convert a raw image into meaningful information. The main objective of image preprocessing is to improve the image quality. It includes the following steps:

- Image Cleaning: Removing Noise from the Thyroid US images (Using Filters).
- Image Normalisation: Standardise image pixel, fine-tune contrast.
- Image Resizing: Adjust images to the same size for consistent input into the machine learning model.

➢ *Image Segmentation:*

Image segmentation involves parting an image into many segments, with each segment displaying a particular portion that is simpler to analyse. The primary goal of segmentation is to make processing and analysing an image simpler.

Below are some techniques used for image segmentation.

- Thresholding: A simple way where pixels are clustered based on their lightness or darkness. The technique works well for images that have clearly different regions.
- Edge-Based Segmentation: Focuses on detecting boundaries between different regions. Techniques like Canny edge detection or Sobel operators are used to highlight edges.
- Region Growing: Starts with seed points and expands the region by adding neighbouring pixels with similar properties.

- Watershed Algorithm: Treats the image as a topographic surface, where regions are segmented by "flooding" the surface from different seed points.

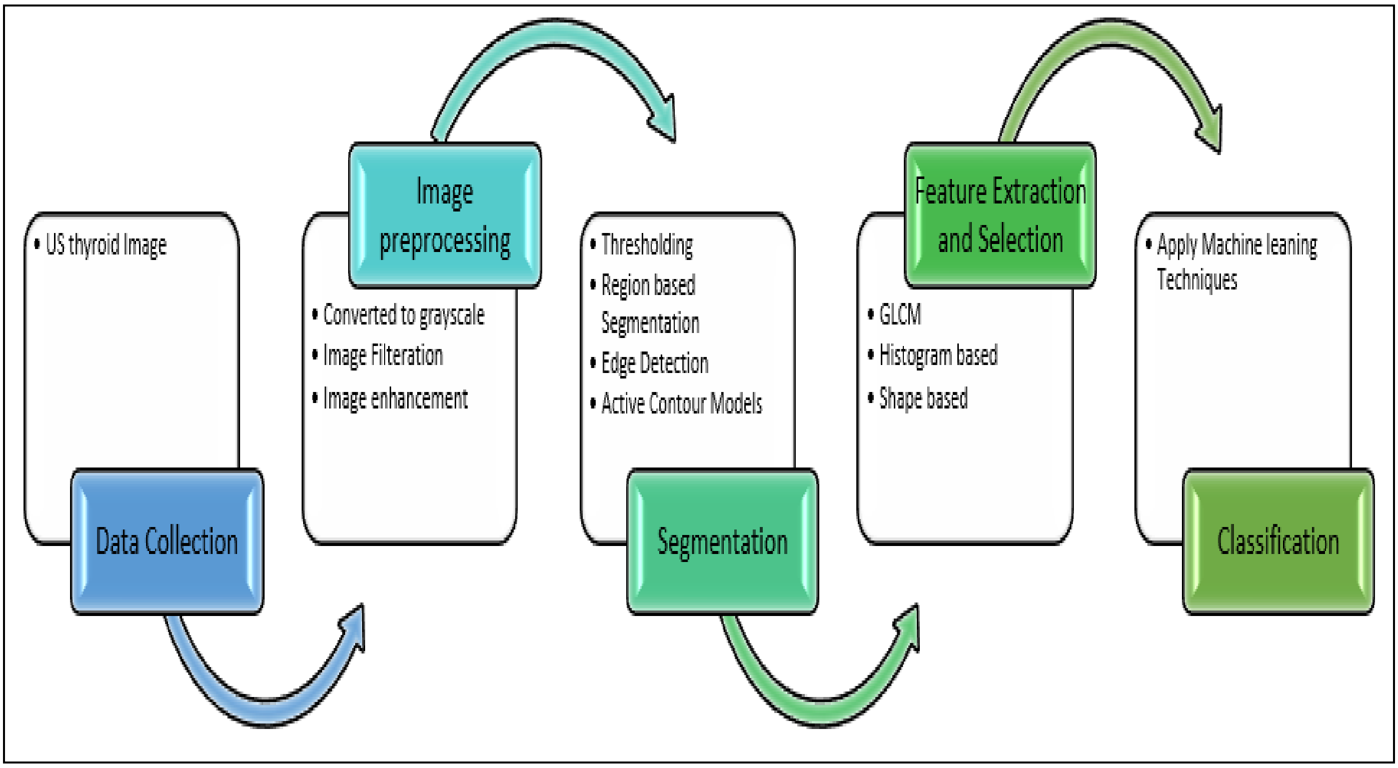

Fig 1 System Flow to Detect Thyroid Cancer

- Clustering Algorithms: Based on pixel similarity, techniques such as K-means clustering separate the image into sections.
- Active Contour Models (Snakes): These evolve a curve or boundary that adjusts to fit the contours of an object within the image, often used for segmenting more complex shapes.

➢ *Feature Extraction:*

Feature extraction is an important step in image processing and computer vision. Identifying and encoding distinctive structures seen in an image is the main purpose of feature extraction. With this process, the image data is changed into numerical formats that maintain the key information. They play a key role in tasks following image processing, including object detection and image classification. There are various techniques used to extract features from the image, like Grey-Level Co-occurrence Matrix (GLCM), Intensity-based feature extraction technique, Histogram-based feature extraction

➢ *Model Training and Evaluation:*

The model training phase is a vital step in developing an AI system to detect thyroid cancer using ultrasound images. In this stage, the model learns to identify patterns by analysing a large set of labelled images showing both cancerous and non-cancerous thyroid nodules. Features like shape, texture, and edges help the model distinguish between benign and malignant cases. By training on this data, the model becomes capable of making accurate predictions, supporting doctors in faster and more reliable diagnoses. Additionally, performance metrics such as accuracy, sensitivity, specificity, and AUC (Area Under the Curve) are closely monitored to fine-tune the model and prevent issues like overfitting or underfitting.

Ultimately, the training phase is where the model begins to mirror the diagnostic abilities of skilled radiologists, potentially serving as a valuable support tool in clinical decision-making.

This study aims to evaluate the efficacy of these filters in suppressing noise while maintaining the structural integrity of ultrasound images. We have analysed the filters' performance based on quantitative metrics, including Peak Signal-to-Noise Ratio (PSNR), mean squared error (MSE) and Root Mean Squared Error (RMSE).

The findings from this study are expected to provide valuable insights into the strengths and limitations of these noise reduction techniques, offering guidance for their practical application in medical imaging and beyond. Through this comparative analysis, we seek to contribute to the ongoing advancements in image preprocessing methods for improving the interpretability and diagnostic accuracy of ultrasound images.

II. PREPROCESSING

Ultrasound imaging is a commonly used diagnostic tool in medical imaging due to its non-invasive nature, real-time imaging capability, and relatively low cost. However,

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ultrasound images are often degraded by various types of noise, like primarily speckle noise, Gaussian Noise, and Salt-and-Pepper Noise, which arises from the coherent interference of ultrasound waves. This noise reduces image quality, obscures anatomical details, and complicates accurate diagnosis. Therefore, effective image preprocessing techniques are crucial for enhancing image quality and facilitating better analysis.

Image preprocessing for noise removal involves the application of filters and algorithms to suppress noise while preserving the essential details and structures in the image. The selection of the appropriate filtering technique is vital, as different filters have varying capabilities to balance noise reduction and detail preservation.

In this research paper, we have explored and analysed the performance of various noise reduction filters applied to ultrasound images. Specifically, we have implemented and compared the following filters:

➤ *Average or Mean Filter:*

Mean filtering is a straightforward, intuitive, and easy-to-implement method for reducing noise in images by minimizing the intensity variation between neighbouring pixels. It is commonly used for smoothing purposes. The concept behind mean filtering is simple: each pixel in the image is replaced with the average value of its surrounding pixels, including itself. This process helps to eliminate pixel values that are inconsistent with their neighbours. Mean filtering is typically considered a convolution operation, involving a kernel that defines the neighbourhood size and shape used to compute the average. A 3×3 square kernel is commonly employed, though larger kernels, such as 5×5 squares, can be used for more extensive smoothing. One of the main challenges of mean filtering is that an outlier pixel with an unusually high or low value can disproportionately influence the average of all pixels within its neighbourhood..

➤ *Median Filter:*

The median filter reduces noise in an image by replacing each pixel with the median value of its surrounding neighbourhood, helping to preserve edges and fine details. Unlike the mean filter, which uses the average of neighbouring pixels, the median filter selects the middle value after sorting the surrounding pixel intensities. This method is effective at maintaining spatial details and removing noise, particularly when fewer than half of the neighbourhood pixels are affected. However, it is less effective with Gaussian noise and computationally more expensive due to the need for sorting.

➤ *Adaptive Median Filter:*

The adaptive median filter addresses the limitations of the standard median filter by using a variable kernel size, leading to better results. Unlike the median filter, it doesn't replace all pixel values with the median. The adaptive filter works in two steps: first, it calculates the median of the kernel, and second, it checks if the current pixel is corrupted by impulse noise (salt and pepper noise). If the pixel is corrupted, it is replaced with the median; otherwise, the original pixel value is preserved, ensuring only noisy pixels are altered.

Implementation of adaptive median filter

Zmin = Minimum gray level value in Sxy.

Zmax = Maximum gray level value in Sxy

Zmed = Median of gray levels in Sxy

Zxy = gray level at coordinates (x, y)

Smax = Maximum allowed size of Sxy

The adaptive median filter works in two Steps denoted

Level A and Level B as follows:

Step A: A1= Zmed - Zmin A2= Zmed - Zmax If A1 > 0 AND A2 < 0,
Go to level B

Else increase the window size

If window size <=Smax repeat level A

Else output Zxy.

Step B: B1 = Zxy – Zmin

B2 = Zxy – Zmin

➤ *Wiener Filter:*

In ultrasound imaging, the Wiener Filter is widely used to reduce speckle noise while preserving crucial details like tissue boundaries and lesions. By adapting to local noise characteristics and minimizing the mean square error (MSE), it effectively enhances image clarity, improves lesion detection, and maintains tissue structure. It operates in the frequency domain to minimize the mean square error between the original and filtered image. It is particularly effective when the noise characteristics are known.

➤ *Bilateral Filter:*

A Bilateral Filter is a type of smoothing filter used in image processing that preserves edges while reducing noise. Unlike traditional filters like the Gaussian blur, which smoothens the entire image, the bilateral filter considers both spatial distance and intensity difference to perform selective smoothing. It Preserves edges while reducing noise. Ideal for applications like image denoising and detail enhancement.

III. RELATED WORK

Sathesh and Rasitha K [1], introduces a nonlinear adaptive median filtering algorithm designed for noise removal in natural images, particularly effective against salt-and-pepper noise. It highlights various denoising techniques and compares their performance based on Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR). The

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adaptive median filter outperforms other methods by preserving important image details while removing noise, although it is computationally intensive. Experimental results validate its superiority in both visual quality and quantitative measures.

Jae-Chern Yoo and Chang Wook Ahn [2] introduce a "blind-Wiener filter" for image restoration, which operates without prior knowledge of the noise and image power spectra, unlike traditional Wiener filters. The method involves averaging multiple Wiener-filtered versions of a corrupted image, each with added random noise, to enhance signal-to-noise ratio (SNR). The approach demonstrates effectiveness in reducing noise and blur, achieving near-optimal restoration performance comparable to traditional Wiener filters while significantly simplifying the estimation process. Experimental results validate its superiority over existing methods, though the process is computationally intensive.

Arin H. Hamad et. al [3] Denoising of medical images by using some filters. This research work evaluates the effectiveness of various filters—Average, Gaussian, Log, Median, and Wiener—for de-noising medical images affected by Poisson, Speckle, and Gaussian noise. Using MATLAB, the filters were applied to two types of images (cell and breast) in JPG and TIF formats. Results were assessed using image quality metrics like MSE, SNR, and PSNR. The Gaussian filter consistently outperformed others in noise removal, achieving the highest PSNR values. The research highlights the importance of filter selection based on noise type and confirms the Gaussian filter's superior ability to restore medical images.

Prashant Dwivedi et al. [4] evaluate different filters to remove four types of noise—Salt and Pepper, Gaussian, Rayleigh, and Uniform—from digital images. Each filter's performance is measured using metrics like Mean Square Error (MSE) and Peak Signal-to-Noise Ratio (PSNR). Key findings: the Median filter is best for Salt and Pepper noise, the Midpoint filter for Gaussian noise, the Arithmetic Mean filter for Rayleigh noise, and the Geometric Mean filter for Uniform noise. This study helps in selecting the right filter to enhance image quality.

Suman Shrestha [5] proposes a novel adaptive median filter to remove impulse noise (salt-and-pepper noise) from images. Traditional methods often blur the image or struggle with high noise densities. The new method adapts the window size dynamically for better performance. Key highlights are the proposed filter excels in preserving image details while reducing noise. It outperforms standard and adaptive median filters, especially for higher noise densities.

The filter is computationally efficient, making it suitable for real-time applications.

This research enhances image processing by effectively addressing noise while maintaining visual clarity.

Hetvi Soni et. al [6] The paper compares standard and adaptive median filters for removing image noise. Adaptive median filters outperform standard filters by dynamically adjusting the filter size, making them effective for high noise levels (above 20%) without losing image details. They are particularly good at handling salt-and-pepper noise, though further improvements are needed for Gaussian noise.

Sheikh Tania et.al [7] compares various image filtering techniques (Mean, Median, Wiener filters, Wavelet, and Curvelet transforms) for reducing noise in aerial images. Each method is evaluated based on its ability to remove noise types like Gaussian, salt and pepper, and speckle noise, using metrics like PSNR and MSE. Key findings show that the Median Filter is best for salt and pepper noise, Wavelet Transform works well for speckle noise, and no single method is universally superior. The study highlights the importance of tailored approaches for effective noise removal.

Hanung Adi Nugroho [8] evaluates seven filtering techniques for reducing speckle noise in breast ultrasound images to improve diagnostic accuracy. The m-homog filter showed the best overall performance, ADMSS was effective for edge detection, and DPAD enhanced contrast for lesion detection. Combining filters is suggested for optimal results. This study supports better breast cancer diagnosis through improved image clarity.

Priscila B. Calíope [9] compares various filters for reducing speckle noise in ultrasound images to enhance image quality. It evaluates techniques like the modified MAP filter, Frost filter, and wavelet-based methods. The Frost filter showed strong performance, while the modified MAP filter offered adaptability based on local homogeneity. These findings aim to improve medical ultrasound imaging for better diagnosis.

Shyh-Kuang Ueng [10] presents a structure-based filtering method to enhance ultrasound images by reducing speckle noise and preserving critical features. The approach involves computing the diffusion tensor at each pixel, classifying the local structures, and applying adaptive filters based on the structure type (e.g., 1D Gaussian for edges, 2D Gaussian for spots). Results show improved noise reduction and edge enhancement compared to traditional methods, with iterative passes refining the output for better quality.

S Pradeep [11] provides a review of various speckle noise reduction techniques used in ultrasound medical imaging. These methods are grouped into three main categories: spatial domain techniques, transform domain techniques, and methods based on convolutional neural networks (CNNs). The review discusses the advantages and limitations of each approach and compares their effectiveness in preserving image quality while reducing noise. Additionally, the paper evaluates metrics like Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE) for these methods to measure their performance.

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IV. EXPERIMENTAL WORK

➢ *Preprocessing Ultrasound Image with Noise Removal*

- *Step 1: Input Image Acquisition:*
- *Step 2: Grayscale Conversion (if Necessary):*

✓ If the input image is in color (RGB), convert the image to grayscale. Most filtering methods work on single-channel intensity images.

- *Step 3: Noise Analysis:*

▪ *Image Preprocessing (Resize or Crop):*

✓ Resize or crop the image if necessary. This step can be useful for consistency or to focus on a region of interest (ROI).
✓ We can resize the image to a fixed size (e.g., 256x256) or crop to focus on specific areas like the thyroid region.

▪ *Adjust Contrast or Brightness:*

✓ Adjust the image's contrast and brightness to enhance image quality. This step helps in making the details more visible for further processing.
✓ We can use methods like histogram equalization or contrast-limited adaptive histogram equalization (CLAHE).

- *Step 4: Noise Removal Using Filters:*

✓ Depending on the type of noise present in the image (e.g., Gaussian noise, speckle noise, salt-and-pepper noise), apply the appropriate noise removal filter.
✓ Average or mean Filter: Useful for removing random noise. It replaces each pixel with the average of its neighbouring pixels.
✓ Median Filter: reduces salt-and-paper noise by replacing each pixel with the median of its neighbourhood, preserving edges effectively.
✓ Adaptive Median Filter: Effective for salt-and-pepper noise, as it adapts based on the local statistics.
✓ Wiener Filter: Suitable for Gaussian noise, it works by minimizing the mean square error between the noisy and clean image.
✓ Bilateral Filter: Effective for speckle noise, preserves edge details.

V. RESULT AND DISCUSSIONS

The study examines various types of noise affecting images, including original, salt-and-pepper, speckle, and Gaussian noise. These images are processed using various filtering techniques to assess their denoising effectiveness. The evaluation metrics used for filter performance include Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Root Mean Square Error (RMSE), with lower values indicating better denoising, higher noise removal, and better performance.

Figure 2 shows the original image alongside versions that have been intentionally altered with different types of noise—paper salt, Gaussian, and speckle. These noisy images mimic the kinds of distortions that often occur in real-world medical imaging, making them useful for testing how well different denoising methods can restore image quality.

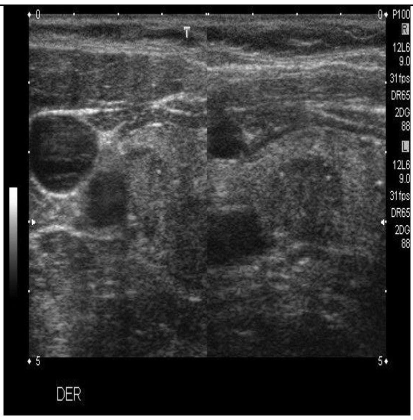
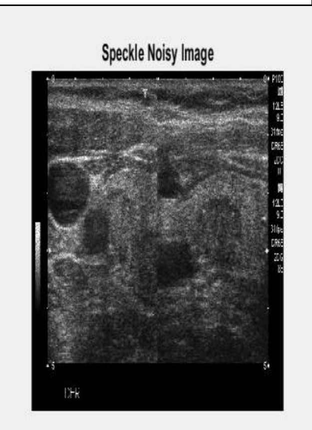
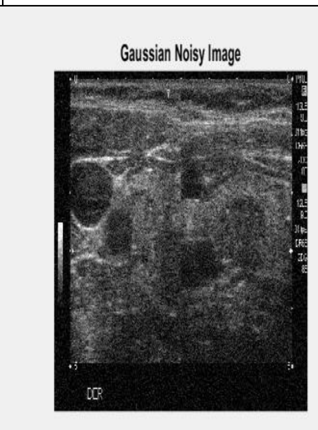
Original Image	Salt-and-Paper noise	Speckle noise image	Gaussian noise image
			
(a)	(b)	(c)	(d)

Fig 2 Image with Noise

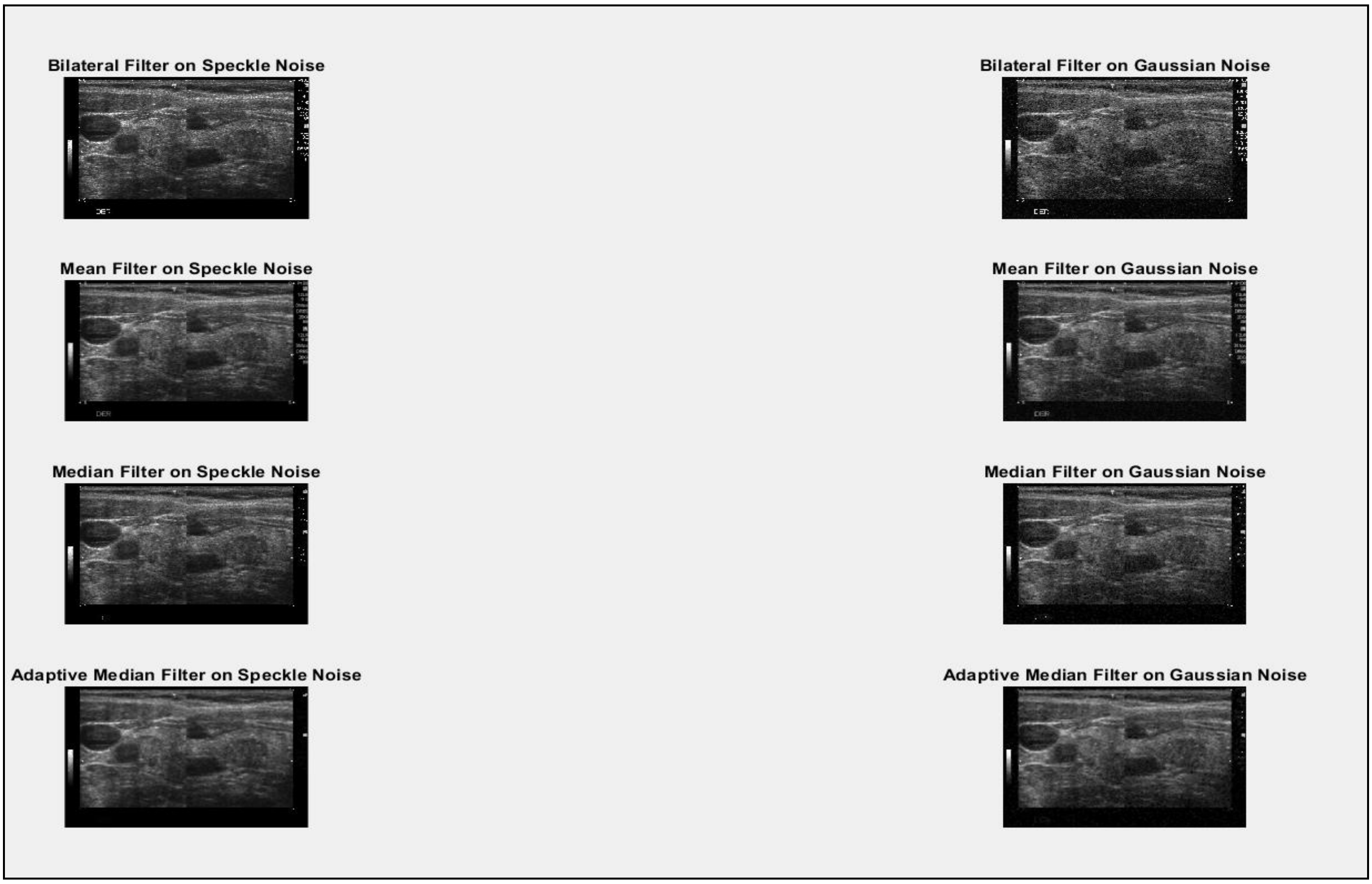


Fig 3 Denoise Images

Figure 3 illustrates the denoised images produced after reducing speckle and Gaussian noise. To achieve this, different filtering techniques were applied, including the bilateral filter, mean filter, median filter, and adaptive median filter. Each of these methods works in a unique way to smooth the image while preserving important details, helping to improve the overall quality of the ultrasound images.

Table 1 shows how the different filters—Bilateral, Mean, Adaptive, and Wiener—performed when tested against speckle and Gaussian noise. Their effectiveness was measured using Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Root Mean Square Error (RMSE). Together, these metrics give a clear picture of how well each filter reduces noise while still preserving image quality, making it easier to compare their strengths and weaknesses under different noise conditions.

Table 1 Parameter Evolution

Bilateral Filter Metrics:						
	MSE		**PSNR**		**RMSE**	
	Speckle Noise	**Gaussian Noise**	**Speckle Noise**	**Gaussian Noise**	**Speckle Noise**	**Gaussian Noise**
Image 1	0.0020858	0.0044828	26.8073	23.4845	0.04567	0.066954
Image 2	0.0017029	0.004209	27.6882	23.7583	0.041266	0.064876
Image 3	0.0018216	0.0040794	27.3955	23.894	0.04268	0.06387
Image 4	0.0021628	0.0040615	26.6499	23.9131	0.046506	0.06373
Image 5	0.0017128	0.0038357	27.6629	24.1616	0.041386	0.061933
Mean Filter Metrics:						
	MSE		**PSNR**		**RMSE**	
	Speckle Noise	**Gaussian Noise**	**Speckle Noise**	**Gaussian Noise**	**Speckle Noise**	**Gaussian Noise**
Image 1	0.0020858	0.0044828	26.8073	23.4845	0.04567	0.066954
Image 2	0.0034496	0.0045128	24.6223	23.4555	0.058733	0.067178
Image 3	0.0036428	0.0047013	24.3856	23.2778	0.060356	0.068566
Image 4	0.0033811	0.0043648	24.7095	23.6003	0.058147	0.066067
Image 5	0.0032305	0.0043566	24.9073	23.6085	0.056838	0.066005
Median Filter Metrics:						
	MSE		**PSNR**		**RMSE**	

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	Speckle Noise	Gaussian Noise	Speckle Noise	Gaussian Noise	Speckle Noise	Gaussian Noise
Image 1	0.0046141	0.0049424	23.3591	23.0606	0.067927	0.070302
Image 2	0.0043943	0.0047823	23.5711	23.2036	0.066289	0.069154
Image 3	0.0044968	0.0048786	23.471	23.117	0.067058	0.069847
Image 4	0.0043999	0.0046152	23.5656	23.3581	0.066332	0.067936
Image 5	0.0040438	0.0044643	23.9322	23.5025	0.063591	0.066815
Adaptive Filter Metrics:						
	MSE		**PSNR**		**RMSE**	
	Speckle Noise	**Gaussian Noise**	**Speckle Noise**	**Gaussian Noise**	**Speckle Noise**	**Gaussian Noise**
Image 1	0.0061162	0.0058895	22.1352	22.2993	0.078206	0.076743
Image 2	0.0057611	0.0056405	22.395	22.4868	0.075902	0.075103
Image 3	0.0061519	0.0059638	22.1099	22.2448	0.078434	0.077226
Image 4	0.0057881	0.0055324	22.3747	22.5709	0.076079	0.07438
Image 5	0.0056195	0.0054694	22.503	22.6206	0.074963	0.073955
Wiener Filter Metrics						
	MSE		**PSNR**		**RMSE**	
	Speckle Noise	**Gaussian Noise**	**Speckle Noise**	**Gaussian Noise**	**Speckle Noise**	**Gaussian Noise**
Image 1	0.0015541	0.0025627	28.0851	25.9131	0.078206	0.039422
Image 2	0.0013646	0.0024649	28.65	26.082	0.03694	0.049648
Image 3	0.0015773	0.0024853	28.0209	26.0463	0.039715	0.049852
Image 4	0.0016019	0.0023598	27.9538	26.2712	0.040023	0.048578
Image 5	0.0014321	0.0024202	28.4403	26.1615	0.037843	0.049195

➢ *The Performance of the Different Filters is Summarized as Follows:*

- *Bilateral Filter :*

The bilateral filter performed quite well, especially with speckle noise where it reached PSNR values of about 26–27 dB. For Gaussian noise, its performance was moderate, with values closer to 23–24 dB. Its lower MSE values show that it removes noise effectively while still preserving edges, which is one of its main strengths.

- *Mean Filter :*

The mean filter gave slightly lower PSNR values, around 24–25 dB, and higher MSE and RMSE values. This suggests that it smooths the image too much, which reduces noise but also blurs out important details. Overall, it is less effective than the bilateral filter.

- *Median Filter :*

The median filter showed the lowest PSNR values, around 23–24 dB, and higher MSE values compared to the others. While it is well known to be effective for salt-and-pepper noise, it did not perform well with Gaussian or speckle noise in this case.

- *Adaptive Filter :*

The adaptive filter had the weakest performance overall, with PSNR values in the range of 22–23 dB and high RMSE values. It tended to over-smooth the image, which made it less effective for noise removal and caused a loss of important details.

- *Wiener Filter (Best Performer) :*

The Wiener filter stood out as the best performer among all methods. It achieved the highest PSNR values, about 28 dB for speckle noise and 26 dB for Gaussian noise, while also giving the lowest MSE values. This means it not only removed noise more effectively but also preserved the finer details of the image, making it the most reliable option overall.

VI. KEY FINDINGS AND COMPARISON

The results show that each filter has its own strengths and weaknesses. The bilateral filter is good at keeping edges sharp, which makes it useful when preserving boundaries is important, though it doesn't perform as well with Gaussian noise. The mean filter smooths images effectively but often blurs out important details, making it less suitable when fine structures need to be preserved. The median filter is very effective for removing salt-and-pepper noise but struggles with Gaussian and speckle noise, limiting its overall flexibility. The adaptive filter gave the weakest results, with poor noise removal and noticeable loss of image quality. In contrast, the Wiener filter performed the best overall, offering the highest noise reduction while still preserving image details, making it the most reliable option across different types of noise.

VII. CONCLUSION

This study explored different preprocessing techniques to enhance ultrasound thyroid images for better cancer detection, focusing on filters such as the Mean, Median, Adaptive Median, Bilateral, and Wiener filters. Their performance was evaluated using Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Root Mean Square Error (RMSE). Among them, the Wiener filter proved to be the most effective, delivering the highest PSNR values (~28 dB for speckle noise and ~26 dB for Gaussian noise) and the lowest MSE. This shows its ability to reduce noise efficiently while preserving important image details. The bilateral filter also performed well, especially in preserving edges, making it useful in situations where maintaining

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structural integrity is crucial, though its noise removal ability was only moderate. On the other hand, the mean filter tended to blur fine details, and the median filter, while effective against salt-and-pepper noise, struggled with Gaussian and speckle noise. The adaptive filter showed the weakest performance, with low PSNR and high MSE, suggesting poor noise removal. Overall, the Wiener filter is the best choice for general ultrasound denoising, while the bilateral filter is more suitable when edge preservation is important. In contrast, the mean and median filters have limited applications in medical imaging, and the adaptive filter is not recommended. These findings emphasize the need to carefully select preprocessing methods based on the type of noise and diagnostic goals in order to improve image quality and support more accurate thyroid cancer detection.

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